Integrated Framework for Light Pollution Assessment and Mitigation: A Multifaceted Approach with TOPSIS and Machine Learning

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Abstract. In this study, we propose the development of an evaluation system to quantify the degree of light pollution and offer three strategies for mitigating its negative effects. Our research identifies 4 distinct types of cities and employs a 16 key indicators to assess the level of light pollution risk, forming the basis for the construction of the Light Pollution Assessment (LPA) Model. Utilizing the TOPSIS and EWM methods, we ranked each city and determined a composite score interval, categorizing pollution levels from I to IV. Our evaluation system designates level I with an overall score of 0.7466, establishing it as a benchmark for assessing the risk level of light pollution. Recognizing that certain factors influencing LPA levels may not directly contribute to light pollution, we introduce the ML-based Strategy Evaluation (MLE) method, this approach classifies 11 out of 16 indices based on their relevance to light pollution. Our analysis reveals that the number of streetlights, the range of ULOR (Upward Light Output Ratio), and the presence of natural protected areas are the top three factors affecting light pollution. With an accuracy of 79.1%, the MLE method demonstrates a strong alignment with the data. Based on our findings, we propose three targeted strategies focusing on luminance regulation, greenery implementation, and legal enhancements to address and alleviate light pollution challenges in urban environments. This research contributes a comprehensive assessment framework and actionable strategies for policymakers and urban planners to effectively manage and reduce light pollution.

Keywords: Light pollution control, TOPSIS, Machine Learning.

1. Introduction

In ancient times, light is considered to represent certainty, safety and warmth. However, the improper use of light has brought adverse impacts to both human and nature. Most environmental pollution on Earth comes from humans and their inventions, affecting human health, wildlife behavior as well[1].It is also clear that given the diversity of sources and ways in which ALAN(artificial light at night)is emitted, and the diversity of ways in which it impacts biological systems, the proportion of the earth over which ALAN occurs at levels at which it is likely to have such impacts is marked.

To measure light pollution, Susan Mander [2] has introduced Many different measures to quantify light, like using satellite data from DMSP/OLS, VIIRS/DNB and luojia-1, or gathering information from the device named SQM. However, Spectral and spatial resolution, together with calibration can be a challenge for the former, while data-logging meters are spatially restricted to a single target for the latter. J.S.Botero developed a low cost pollution measurement station with sensors and tensorflow model with an average error of approximately 2.67%[3]. Fabio F warned that [4] the growth of light pollution is difficult to discern with satellites now in operation, since their detectors are blind to the blue light emitted by LED, which means the traditional methods are outdated and new ways to quantify the extent of light pollution are urgently needed [5].

TOPSIS model has been widely used to build evaluation systems with many indicators. Xiaoyun Z [6] built a food security evaluation system containing 25 indicators, conducting evaluation and research on the evolution and current situation of China’s food security. Hu Shengde[7] made a performance analysis of marine ecological environment governance based on DPSIR and entropy weight TOPSIS model, emphasizing the huge influence of pressure factors such as ecological environment, population, and economy. Jiong Li [8] introduced an ecological vulnerability assessment method of scenic spots based on TOPSIS model and spatial principal component analysis, which reached an accuracy of 98%. Literature mentioned that currently the world has not yet formed a unified technical standard for light pollution, and the current global technical regulations and guidelines regarding light pollution primarily center on restricting brightness and illuminance, with a focus on aspects related to lighting design. Therefore, it is necessary to establish a multi-factor prediction model to help fill the research gap.

Compared with the existing literature, by using the data from COMAP, this article not only fills the knowledge gap on how to measure the level of light pollution without the data from satellites, but also creates an standard that can be widely applied from cities to rural areas. Also, various key indicators are chosen to formulate a quantitative model for the risk level of light pollution. What's more, considering that the correlation between certain factors and light pollution is not inherently strong, machine learning method is employed for filtering, enhancing the precision of the results. Finally, three strategies focusing on luminance regulation, greenery and complement of law are introduced, which may provide guidance for the governance of light pollution in daily life.

2. Light Pollution Assessment(LPA)Model

2.1. The Entropy-TOPSIS method

Selecting an appropriate evaluation method for light pollution standard is a complex task, therefore the modified Entropy-TOPSIS method is chosen to solve this Multiple Attribute Decision Making (MADM) problem. All the data are analyzed with the method and will be took the vegetation cover(V) as an example to explain our ideas.

2.1.1 Calculate weights - EWM.

EWM (Entropy weight method) can measure the amount of useful information with the data provided. It is an objective way for weight determination when several interrelated objects are evaluated at the same time.

Our evaluation system includes 16 indices ($G_1, G_2, \dots G_{16}$) and 200 cities ($V_1, V_2, \dots V_{200}$). $A=(a_{ij})_{200x16}$ is the decision matrix and $a_{ij}(1 \le i \le 200, 1 \le j \le 16)$ is the index value.

$$A=\begin{bmatrix} a_{11} & a_{12} & \dots a_{1n} \\ a_{21} & a_{22} & \dots a_{2n} \\ & \dots & \\ a_{m1} & a_{m2} & \dots a_{mn} \end{bmatrix} \quad (1)$$
$$(n=16, m=200)$$

Since the data are consisted of both benefit indices and cost indices, standardization is an essential part of data normalization. The decision matrix A is transformed into standardized matrix $B=(b_{ij})_{mxn}$. The formula (2) is shown below:

$$Benefit\,indices \begin{cases} b_{ij}=\dfrac{a_{ij}-\min\limits_i a_{ij}}{\max\limits_i a_{ij}-\min\limits_i a_{ij}} & ,\max\limits_i a_{ij} \ne \min\limits_i a_{ij} \\ b_{ij}=1 & ,\max\limits_i a_{ij} = \min\limits_i a_{ij} \end{cases} \quad (2)$$

$$Cost\,indices \begin{cases} b_{ij}=\dfrac{\max\limits_i a_{ij}-a_{ij}}{\max\limits_i a_{ij}-\min\limits_i a_{ij}} & ,\max\limits_i a_{ij} \ne \min\limits_i a_{ij} \\ b_{ij}=1 & ,\max\limits_i a_{ij} = \min\limits_i a_{ij} \end{cases} \quad (3)$$

Then calculate the normalization matrix(pij), in order to obtain the entropy weight of each indicator. The entropy weight(ej) of the jth index is:

$$p_{ij} = \frac{b_{ij}}{\sum_{i=1}^{200} b_{ij}} \tag{4}$$

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij}\ln(p_{ij}) \qquad m = 200 \tag{5}$$

Calculate the coefficient of variation d_j of each index. The greater the impact of the index on light pollution, the larger the corresponding weight coefficient. For each index, the larger that the coefficient of variation d_j, the smaller that E_j will be.

$$d_j = 1 - e_j \tag{6}$$

Finally, normalize the weight vector (w_j), where w_j is determined as:

$$w_j = \frac{h_j}{\sum_{j=1}^{n} h_j} \tag{7}$$

2.1.2 TOPSIS-based Data Analysis

TOPSIS (The Technique for Order Preference by Similarity to Ideal Solution) is based on the fundamental premise that the best solution has the shortest distance from the positive-ideal solution, and the longest distance from the negative-ideal one. It has been used extensively with more than 14000 citations, including areas such as decision making, quality assessment and so on.

The TOPSIS method can be explained as the steps shown below:

Firstly, normalize performance ratings. In this procedure, each performance rating is divided by its norm. The normalized ratings y_{ij} can be calculated by a_{ij} in 2.1.1.

$$y_{ij} = a_{ij} / \sqrt{\sum_{i=1}^{I} a_{ij}^2} \tag{8}$$

The normalized performance ratings y_{ij} and the weighted ratings w_{ij} are combined to form the weighted-normalized decision matrix Z.

$$Z = \omega_j * y_{ij} = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1m} \\ z_{\dots 1} & \cdots & \cdots & \cdots \\ z_{n1} & z_{n2} & \cdots & z_{nm} \end{bmatrix} \tag{9}$$

Secondly, find positive and negative ideal solutions. And describe Z^+ and Z^- as the positive and negative ideal solution sets, the calculation method is listed below:

$$Z^+ = (Z_1^+, Z_2^+, \dots, Z_m^+) = (\max\{z_{11}, z_{21}, \dots, z_{n1}\}, \max\{z_{12}, z_{22}, \dots, z_{n2}\}, \dots, \max\{z_{1m}, z_{2m}, \dots, z_{nm}\} \tag{10}$$

$$Z^- = (Z_1^-, Z_2^-, \dots, Z_m^-) = (\min\{z_{11}, z_{21}, \dots, z_{n1}\}, \min\{z_{12}, z_{22}, \dots, z_{n2}\}, \dots, \min\{z_{1m}, z_{2m}, \dots, z_{nm}\} \tag{11}$$

Thirdly, Obtain the distance. The distance of each alternative rating from both the positive and the negative ideal solutions are measured, which is obtained by applying the distance theory. The formula is:

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \omega_j (Z_j^+ - z_{ij})^2} \tag{12}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} \omega_j (Z_j^- - z_{ij})^2} \tag{13}$$

Lastly, calculate the overall preference score. The overall preference score d_i for each alternative is obtained as shown below:

$$d_i = \frac{s_i}{\sum_{i=1}^{n} s_i} \tag{14}$$

2.1.3 Definition of LPA risk level

Data of 200 locations around the world are collected, including 4 categories (economy & culture, environment, transportation, performance of luminaire). An evaluation index system (LPA model) including 16 indices and 4 categories is established. Based on Entropy-TOPSIS method, the system is modified according to the characteristics of the data. Also, by analyzing the result by arithmetic progression, a comprehensive light pollution evaluation system is set up, and could be broadly applied.

Based on EWM, the entropy weight and information utility of the 16 indices are calculated. The results are as shown in Table.1:

Table.1. Indices affect light pollution level.

<table>
<tr><th>Indices(I)</th><th>Information utility results d</th><th>weights(%)</th><th>Indices(II)</th><th>Information utility results d</th><th>weights(%)</th></tr>
<tr><td rowspan="3">Environment</td><td rowspan="3">0.248</td><td rowspan="3">15.828</td><td>Ratio of rainy and cloudy days in a year</td><td>0.01</td><td>0.619</td></tr>
<tr><td>Vegetation cover</td><td>0.056</td><td>3.569</td></tr>
<tr><td>Natural protected Area</td><td>0.182</td><td>11.64</td></tr>
<tr><td rowspan="5">Economy and Culture</td><td rowspan="5">0.622</td><td rowspan="5">39.758</td><td>Range of ULOR</td><td>0.032</td><td>2.074</td></tr>
<tr><td>Foundation of observatory</td><td>0.2</td><td>12.801</td></tr>
<tr><td>Population</td><td>0.108</td><td>6.884</td></tr>
<tr><td>GDP</td><td>0.092</td><td>5.875</td></tr>
<tr><td>Legislation against light pollution</td><td>0.19</td><td>12.124</td></tr>
<tr><td rowspan="4">Transportation</td><td rowspan="4">0.456</td><td rowspan="4">29.1</td><td>The number of ports</td><td>0.08</td><td>5.084</td></tr>
<tr><td>Annual throughput of airport</td><td>0.13</td><td>8.297</td></tr>
<tr><td>The number of streetlights</td><td>0.083</td><td>5.31</td></tr>
<tr><td>Annual throughput of railway station</td><td>0.163</td><td>10.409</td></tr>
<tr><td rowspan="4">Performance of local luminaire</td><td rowspan="4">0.241</td><td rowspan="4">15.313</td><td>Luminance uniformity</td><td>0.05</td><td>3.187</td></tr>
<tr><td>Minimum color temperature</td><td>0.046</td><td>2.908</td></tr>
<tr><td>Maximum color temperature</td><td>0.022</td><td>1.385</td></tr>
<tr><td>LAV</td><td>0.123</td><td>7.833</td></tr>
</table>

The results indicate that the top three indicators of light pollution are ‘La (law against light pollution)’, ‘Fo(foundation of observatory)’ and ‘N(natural protected area)’ ,which are given weights of 12.124%,12.801% and 11.64%.

Astronomy is very sensitive to light pollution. The night sky viewed from a city bears no resemblance to what can be seen from dark skies. Concerning that observatories are built in sparsely populated areas due to the adverse effect of skyglow, decide to replace this factor by ‘Ar(Annual throughput of railway station)’.

In the process of TOPSIS-based Data Analysis, 15 were selected out from the 200 cities to show the results and the 15 cities are shown in Table .2.

Table.2. LPA -score analyzed by TOPSIS model.

Index value	D_i+	D_i-	Overall preference score	Index value	D_i+	D_i-	Overall preference score
Munich	0.6449	0.6222	0.4910	L.A.	0.3493	0.7823	0.6914
Tokyo	0.3376	0.8172	0.7077	Beijing	0.4846	0.7456	0.6061
Shanghai	0.4845	0.7383	0.6038	New York	0.3097	0.8295	0.7282
Chengdu	0.4897	0.7042	0.5898	Paris	0.4657	0.7460	0.6157
Orlando	0.6120	0.6366	0.5099	Haikou	0.6782	0.5359	0.4414
Seattle	0.5787	0.6765	0.5390	Dakar	0.6128	0.5971	0.4935
Ottawa	0.5928	0.6301	0.5153	Riga	0.6101	0.6100	0.4999
London	0.4744	0.7402	0.6094				

Traditional sky brightness level is set up by International Commission on Illumination (CIE), from which a rough insight of the luminance standards can be gained. However, considering the potential impact of human activity and natural environment, a more comprehensive evaluation system of light pollution is in urgent need.

Therefore, based on the results, the conclusion is drawn, and the score is divided into 4 categories as what Table.3 shows.

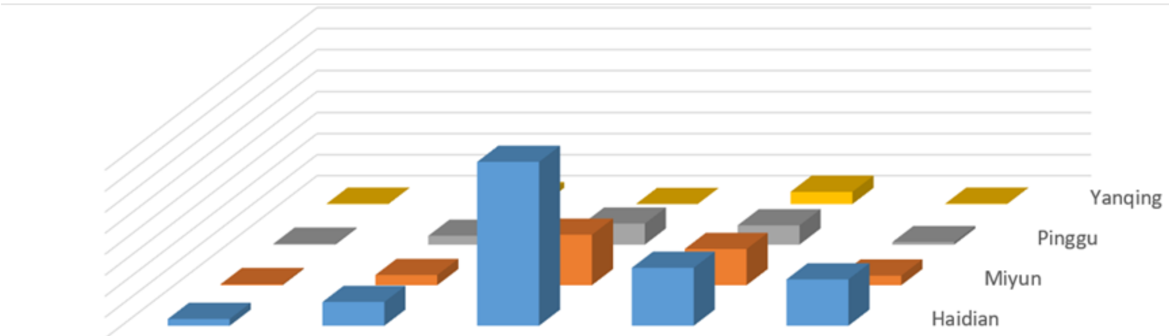
Table.3. Risk level.

Risk level	Score range
LPA I	0.5649~1
LPA II	0.4017~0.5649
LPA III	0.2384~0.4017
LPA IV	0~0.2384

According to the maximum and minimum score of 200 cities, LPA introduces a assessment system, the maximum score of LPA IV is 0.2384 after which adds the same value of 0. 1632.The higher the score is, the more risk of light pollution.

2.2. LPA Validation ---4 districts in Beijing

In order to reduce the impact of light pollution, LPA model is applied to 4 districts in Beijing, China, for Beijing is a suitable place consists of four types of places for researching light pollution control. The districts are Yanqing (Protected land), Pinggu (Rural community), Miyun (Suburban community), Haidian (Urban community). And some key attributes are shown in Fig 1.



	Population（10^5）	GDP（10^5）	Annual throughput of airport（10^5）	The number of streetlights（10^6）	Annual throughput of railway station（10^5）
Haidian	323.7000	1132.2857	7800.00	2758.32	2208.44
Miyun	50.3000	485.7143	2400.00	1723.32	458.23
Pinggu	46.2000	419.2714	1000.00	918.32	120.89
Yanqing	15.7000	278.9857	0.00	583.21	18.44

Fig 1. Information about the 4 districts in 3D bar-chart

The data including 16 indices is collected and analyzed with the LPA method. The overall results indicate that the risk level of Haidian is LPA I (0.7466), indicating that light pollution has become a serious problem in this area. Then Miyun’s risk level is LPA II (0.4181), while Pinggu and Yanqing are far from light pollution, both of which are LPA III (0.3058 / 0.2814).

In a general view, the risk level of light pollution goes up as the area becomes more modernized and developed, so the conclusion is drawn that the result matches well with LPA. However, according to the relevant report of National Forestry and Grassland Administration, Yanqing is a protected land with 79% vegetation cover, so at the first sight it would probably be classified into LPA IV.

The reasons behind the cognitive error lie in two aspects. Firstly, luminance uniformity and LAV data are collected from authoritative satellite maps, but the potential figure error is still unavoidable. At the same time, Beijing is a big city of prosperity and vitality, no exception for Yanqing district. The scale of protected area in Yanqing accounts for less than 30 percent, making the cognitive mistake a possible outcome.

3. ML-based Strategy Evaluation (MLE) Method

3.1. Machine-Learning Method of evaluation factors

Based on literature and news, 11 indices in Table 1 are evaluated, and introduced Multiple Linear Regression (MLR) to MLE model mainly to clarify the weight of each factor.

3.1.1 Assumptions of MLR

Homogeneity of variance indicates that the size of the error in our prediction has no significant impact. Independence of observations ensures that all the independent values are not too correlated with each other. Normality suggests that the data follows a normal distribution. Linearity refers to the line of best fit through the data points being a straight line, rather than a curve or some sort of grouping factor.

3.1.2 Calculate weights---MLR.

The formula for a multiple linear regression is shown below:

$$y = \beta_0 + \beta_1 X_1 + ... + \beta_n X_n + e \tag{15}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \in [0,1] \tag{16}$$

$$VIF_i = \frac{1}{1 - R_i^2} \tag{17}$$

y represents the predicted value of the dependent variable, and $\beta_n X_n$ is the nth regression coefficient, while e means the model error, e.g. the variation in our estimate of y.R^2 is positively correlated to the efficiency of a model, if R^2 is close to 1, then the model is suitable for the data. VIF is a common simple stat used to quantify multicollinearity in least squares regressions. It tech1, thennnnnny measures how much the variance of an estimated regression coefficient is increased because of collinearity. The MLR model is used to predict the original data [9], and the fitted graph (Fig 2) is as follows.

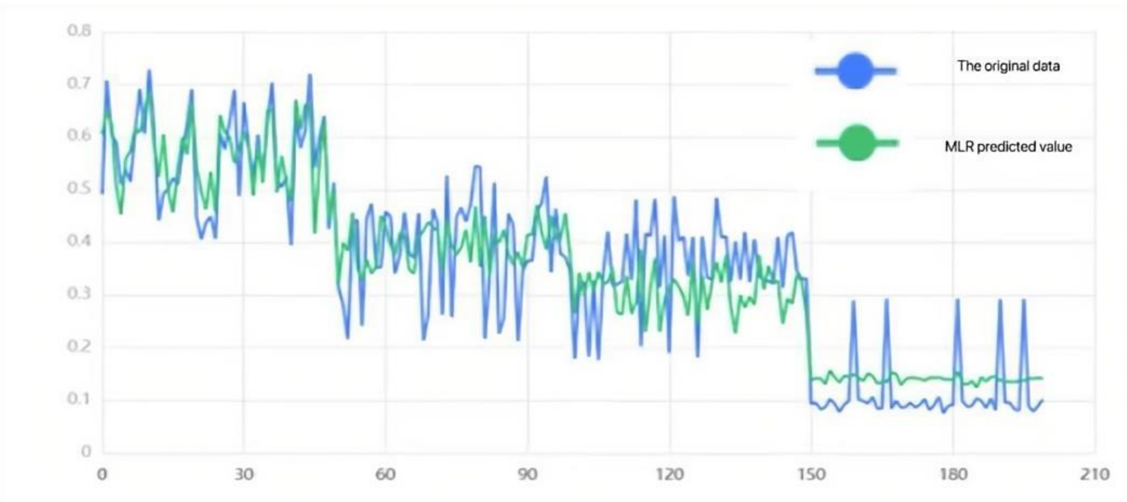


Fig 2. Relativity between original data and MLR predicted value.

With MLR the data is analyzed, and the results are shown in the following table (Table.4).

Table.4. Linear regression analysis results table

Symbol	Indices	Standardized Coefficient Beta	VIF	R^2
R	Ratio of rainy and cloudy days in a year	0.036	1.088	0.791
V	Vegetation cover	-0.097	3.246	
N	Natural Protected Area	-0.182	1.281	
R_u	Range of ULOR	0.227	4.798	
P	Population	0.148	3.746	
N_P	The number of ports	0.077	3.987	
L_a	Legislation against light pollution	-0.105	1.234	
A_r	Annual throughput of railway station	0.068	14.403	
A_a	Annual throughput of airport	-0.036	9.122	
G	GDP	-0.004	3.01	
N_s	The number of streetlights	0.264	14.864	

After the process of MLR, The MLE method model results in the formula below:

$$\begin{aligned} y = {} & 0.27 + 0.041 * R(\%) - 0.083 * V(\%) - 0.067 * N + 0.499 * Ru + \\ & 0.01 * P(10^4) + 0.006 * NP - 0.04 * La + 0.0 * Ar(10^4) - \\ & 0.013 * Aa(10^8) - 0.003 * GDP(10^{12}) + 0.002 * NS(10^4) \end{aligned} \tag{18}$$

3.2. Assessment of Factors

Light pollution is caused by inefficient or excessive use of artificial light because of human activity [10], including over-illumination, sky glow and so on. The specific influencing factors and weights are shown in Table.5. Usually, over-illumination contributes to most of light pollution, and it stems from some factors. Firstly, improper design of buildings produces higher levels of light than people actually need. Secondly, replacing the old streetlamps by LED of higher efficiency will increase the luminous efficiency (in lumens per-watt) to 30 percent and makes that sky glow impact 1.5~3 times bigger than the original. Thirdly, many places do not have certain law against light pollution and complete regulation about the use of lighting techniques. What’s more, there is a growing demand for ‘Daylight Lighting’ due to the need of attracting customers and reducing crime at night.

Table.5. Linear regression correlation coefficient of each factor

factors	weights	factors	weights
The number of streetlights (Transportation)	0.264	Natural Protected Area (Environment)	-0.182
Range of ULOR (Economy and culture)	0.227	GDP (Economy and culture)	-0.004
Population (Economy and culture)	0.148	Annual throughput of airport (Transportation)	-0.036
Annual throughput of railway station (Transportation)	0.131	Legislation against light pollution (Economy and culture)	-0.0105
The number of ports (Transportation)	0.077	Vegetation cover (Environment)	-0.097
Ratio of rainy and cloudy days in a year (Environment)	0.036		

Concerning that the performance of local luminaire and the number of observatories is the result of light pollution, some indices are eliminated, and 11 highly relevant indices are listed above. According to the results in 3.1.2, the number of streetlights is the biggest factor that influences light pollution. Then comes to the range of ULOR and the existence of natural protected area, so based on the result three strategies can be proposed.

3.3. Luminance Regulation

3.3.1 Actions in Detail

To effectively control and prevent light pollution, it is necessary to start from the origin of lighting, which means the planning and design of city lights as well as the development of related industry regulations. This is also the key to implementing the principle of prevention as the primary approach to prevention and control. Specifically, community officials or local organizations can develop measures to regulate manufacturers, control the upward light output ratio (ULOR) of the luminaire during the production process.Also, city designers should try to reduce the number of streetlights as much as possible when planning.

The paper assumes that for the four different types of locations collected previously, a total of 200 cities, the two indicators of range of ULOR and the number of streetlights are each reduced by twenty percent, and the result is that after the indicator change, the effective number of urban communities, suburban communities, rural communities, and ecological areas are 21, 28, 18, and 5, respectively, and the following is a visualization of the effective proportion of the indicator change for each area The following Fig 3 is a visualization of the effective proportion of each region.

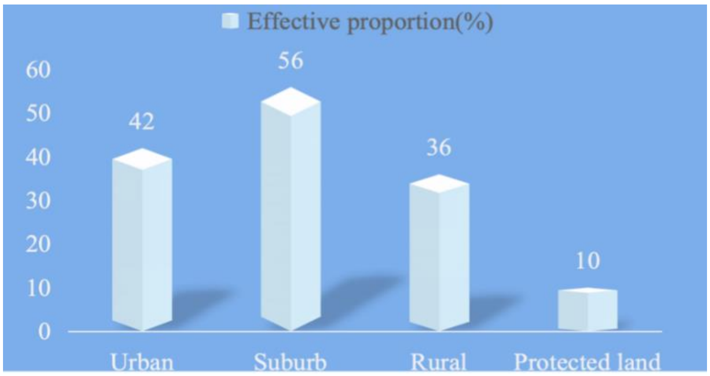


Fig 3. Effectiveness for four types of cities

3.3.2 Potential Impacts--Rising Crime

It's widely acknowledged that robbery and murder are more likely to happen in dark places than in Daylight. Therefore, paper collected light pollution data of 50 cities with the highest crime rate, like Memphis and Detroit. With MLR, paper found that despite some reasonable error, light pollution risk level is negatively correlated to crime rate. The relationship is shown in Fig 4.

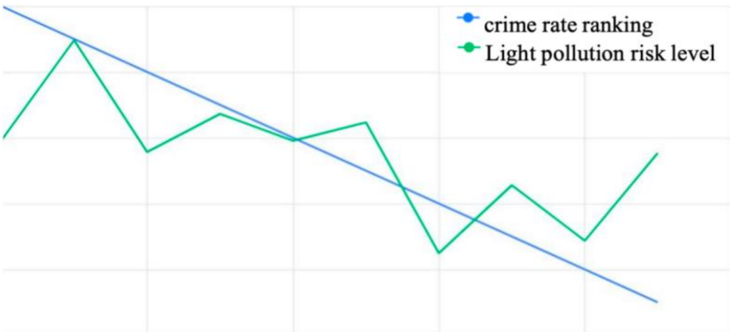


Fig 4. Negative relationship between crime rate and light pollution

The average light pollution risk level is about 0.2311, which means IV level in LPA model.This is because most of the 50 cities with high crime rate are located in the more developed regions of each country, including several capital cities. As a result, the level of light pollution risk tends to be higher, but this does not contradict the fact that there is an inverse correlation between crime rate and light pollution levels.

3.4. Greenery Project

The indirect effect of pollution on plant adaptation may depend on the conservation status of adjacent natural habitats, and tree cover seems to be the main factor affecting plant adaptation in low light pollution sites. Therefore, it is necessary to reduce light pollution by planting trees, planning natural ecological zones, and protecting plant and animal diversity.

Among them, planting trees is a simple but effective way to combat light pollution. Planting trees in strategic locations can reduce the amount of light that enters our living spaces and ecosystems. In addition, trees can absorb carbon dioxide and releasing oxygen. This helps to reduce the greenhouse gas emissions that contribute to climate change, and climate change leads to the adverse change of the ratio of rainy and cloudy days in a year, which is a major cause of light pollution.

Paper assumes that the vegetation cover is increased by twenty percent for the four different types of sites previously collected, for a total of 200 cities, and that additional protected areas are established in areas where no nature reserves have been established, resulting in an effective number of urban communities, suburban communities, rural communities, and ecological areas of 22, 29, 24, and 1, respectively, after the indicator change, and the following Fig 5 is the effective proportion of the indicator change for each area visualization presentation.

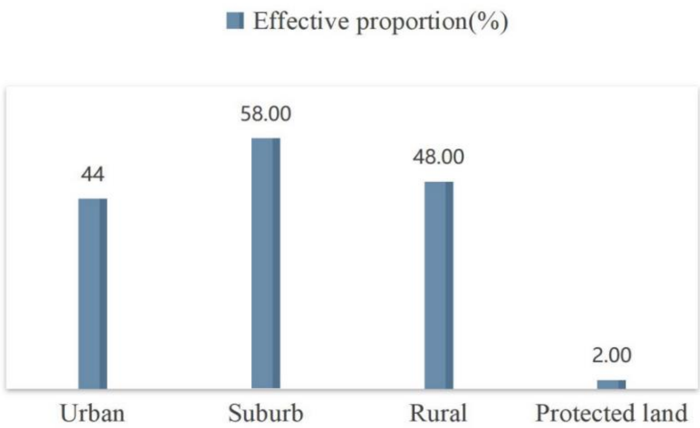


Fig 5. Effectiveness for four types of cities

The planting of vegetation and the construction of natural ecological reserves will affect the construction of industrial parks and commercial plazas in the area, which will inevitably lead to economic problems such as stagnation of regional development and decrease in GDP.

3.5. Complement of law

To pay attention to the issue of light pollution is not nitpicking in ecological conservation work but reflects the environmental management concept of focusing on human-centricity. Legislation for the prevention and control of light pollution should be on the agenda of local organizations and the national government. This would promote the establishment of light environment protection standards based on human health, and even encourage to tax individuals and enterprises who contribute to light pollution for environmental protection purposes.

For the previously collected four different types of locations and a total of 200 cities without legislation on light pollution, paper assumes that they have introduced relevant laws and regulations, and the results yield the effective numbers of urban communities, suburban communities, rural communities, and ecological zones after the indicator change are 29, 25, 28, and 49, respectively. The following Fig 6 is a visual presentation of the effective proportion of the indicator change on each area.

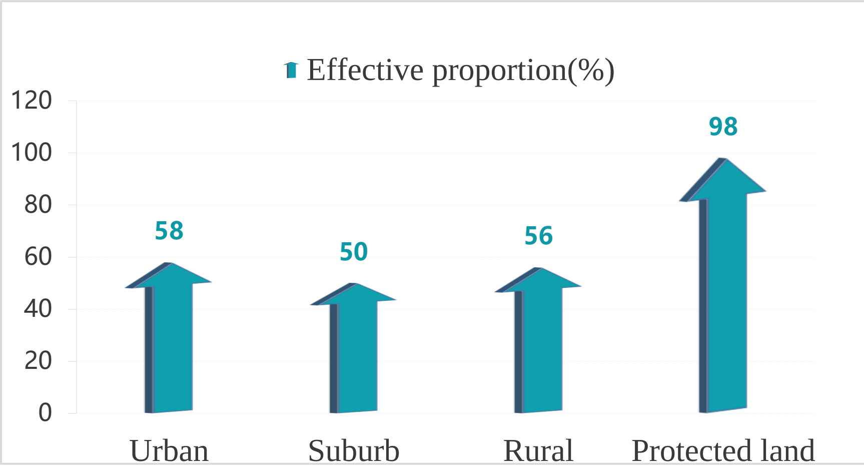


Fig 6. Effectiveness for four types of cities

In urban areas, it's essential for shopping malls and tourist attractions to set up bright illumination, in order to attract more customers, while for factories and ports,lights at night is of great importance for productivity.To be more serious, the complement of law is to some degree, a limit for economic growth.Countries and regions have to slow down to meet the standards,which is a challenging task especially for developing countries.So in strict legislative controls on light usage would inevitably lead to a decrease in industrial and agricultural output, which would not be conducive to local economic growth.

4. Conclusion

This article aims to address the significant issue of light pollution, which has negative impacts on both human health and the natural environment. Through a systematic approach involving four distinct tasks, we successfully developed a Light Pollution Assessment (LPA) model that incorporates 16 key indicators for evaluating the light pollution risk levels in 200 cities worldwide. Initially, our focus was on the identification and quantification of these indicators, leading to the construction of the LPA model using the TOPSIS and EWM methods. The model provides a reliable classification method for categorizing cities into light pollution risk levels (I to IV) based on the composite scores.

Subsequently, the model was applied to four districts in Beijing, China, highlighting Haidian district as experiencing the most severe light pollution (LPA level I). This underscores the practical application value of our assessment system. Following this, we introduced the Machine Learning-based Strategy Evaluation (MLE) method to classify indicators based on their relevance to light pollution. The three most crucial factors——the number of streetlights, the range of ULOR, and the presence of natural protected areas——guided the development of effective mitigation strategies.

In conclusion, our multidimensional research and analysis provide a robust framework for assessing, understanding, and mitigating light pollution. Tailored strategies can be developed globally to promote sustainable and environmentally conscious urban development based on specific circumstances.

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